Original scientific paper

Productivity and Utilization Benchmarks for Chain Flail Delimber-Debarkers-Chippers Used in Fast-Growing Plantations

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Abstract

The study developed robust benchmark figures for the performance of delimber-debarker-chippers in fast-growing eucalypt plantations, through the analysis of an exceptionally large database that combined automatically-captured and user-input records. Data for three Peterson Pacific DDC 5000 H units operated by the Brazilian company Fibria Cellulose were captured continuously for three years, from 2015 to 2017. During this time, all study machines ran triple-shift and clocked over 25 000 hours each. The consolidated record included information for 79 858 delay events, with an average duration of 0.55 hours per event. Delay time accounted for 57% of total worksite time: mean utilization was therefore 43%. Maintenance was the most important cause of delays, and accounted for 22% of total worksite time. Interaction delays came second, and represented 20% of total worksite time. Mean productivity was 88 solid m^3_{ub} (under bark) per productive machine hour (PMH) or 39 solid m^3_{ub} per scheduled machine hour (SMH), depending on whether delay time was excluded or included in the calculation. The gap between the most efficient and the least efficient operator was 22% and 26% for scheduled productivity and utilization, respectively (this difference was calculated by taking the figures for the lowest performer as a basis). While the exact productivity figures reported here may reflect the exceptionally favorable conditions encountered in rationally-managed South American plantations, the dynamics revealed in this study may have general validity and could offer precious insights for rationalizing a whole range of similar operations.

Keywords: logging, utilization, delays, eucalypt, efficiency, chipping

1. Introduction

Plantation forestry covers a much smaller area than conventional forestry, but already accounts for about half of the global supply of industrial wood (FAO 2015). That is the result of a strong focus on production, and a deliberate effort to optimizing all steps in the production process – both of which are peculiar characteristics of modern tree farms. Given the growing demand for fiber products, plantation forestry is expanding rapidly: experts predict that the total area planted with tree farms may soon double (Portin and Lehtonen 2012) and that plantation forestry may account for 75% of the global wood supply by 2050 (Sohngen et al. 1999). Compared with natural forests, modern tree plantations offer many advantages, including rationalized management, vicinity to the conversion plants and pre-defined product targets (Campinhos 1999). Furthermore, industrial tree plantations are generally established with genetically selected propagation material under favorable soil and climate conditions, which result in exceptional growth rates (Stape et al. 2010).

Industrial tree plantations come in many types and they are designed to produce a wide range of wood-based products for use in the building, furniture and sawmilling sectors. However, these plantations play an especially important role in the supply of industrial fiber, used for manufacturing pulp and paper products. In that regard, the most successful examples come from the southern hemisphere, and especially from South America, South Africa and Australia (FAO 2009).

Brazil represents perhaps the most successful case for the application of this new production model. Brazilian tree farms cover 7.8 million hectares and yield

206 million m^3 of round wood per year (IBA 2017). Nor is the role of Brazilian plantations limited to fiber supply alone: plantation forestry offers a recognized contribution to the economic and social development of the Country, while representing one of the most effective measures for offsetting the substantial increase in CO_2 emissions (Machado et al. 2015) caused by rapid industrialization (Rochedo et al. 2016). Yet, fast growing tree plantations attract the interest of other countries, also in the Northern Hemisphere – as proved by the large areas planted with eucalypt in Portugal and Spain (Cerasoli et al. 2016), or the strong predicted role of tree farms in recent EU biomass supply plans (Hesch 2009). Therefore, the Brazilian example used in this study may be considered of general interest, and the main results presented later in the paper may be used for other similar cases, after adjusting for the inevitable differences.

Regardless of the region concerned, tree farms have general characteristics, especially when they are established for fiber production. Relatively small tree size is one of them, and it has important consequences on production efficiency. While trees planted for structural products cannot be harvested until they are big enough to reach the minimum size specification of the target log sorts, trees grown for raw fiber can be harvested much earlier, and as soon as the mean annual increment reaches its peak (Bakker and Nel 2000). Such strategy achieves maximum yield and allows for faster returns on the initial investment, but it has one main drawback: it offers a crop of relatively small trees, with negative effects on harvesting productivity. Indeed, the productivity of conventional single-stem harvesting techniques is directly proportional to stem size, and is especially low in pulpwood-size plantations (Lambert and Howard 1990). If that is the case, then mass handling is the best solution, because it can largely offset the small stem size constraint encountered when harvesting pulpwood plantations (Adebayo et al. 2007, Bisson et al. 2013, Spinelli et al. 2014). Mass handling is normally obtained by deploying feller-bunchers, grapple skidders and chain-flail delimbers debarkers-chippers, which can achieve a remarkably high efficiency even when negotiating small trees (Spinelli et al. 2018).

Countless studies have investigated the productivity of these machines, since good operational planning is based on a reasonably accurate knowledge about the performance that can be expected from the equipment deployed for the task. Recent work has focused on delimbers-debarkers-chippers (DDCs) for two reasons: first, because these machines have not been covered as thoroughly as feller bunchers or skidders, and second because they seem to have a remarkable potential also for those regions where they are not in current use. DDCs are multi-stem processing machines that integrate two functional elements: a chain-flail delimber-debarker and a chipper. The former knocks off branches and bark from whole trees by using hardened chain links mounted on fast-rotating drums (Watson et al. 1993), while the latter turns bark-free stem wood into clean pulp chips. These machines may achieve a productivity of more than 40 t per productive machine hour, and easily remove all limbs and most of the bark (Franklin 1992, Hartsough et al. 2002, Stokes et al. 1989). While somewhat coarse, flailing can be fine-tuned to minimize fiber losses, which are generally lower than 5% (Gingras 1992, Hartsough et al. 2000, Stokes and Watson 1991).

Prospective users can source lots of useful information about these machines from a stream of recent publications specifically dealing with their performance (Ghaffaryian et al. 2013, McEwan et al. 2017, 2018). However, the results contained in these reports are all obtained from relatively short-term studies and they offer reasonably good figures about work productivity but fall short when it comes to long-term machine utilization, which is equally relevant to operation costing and scheduling.

Therefore, the goal of this study was to produce a robust general benchmark for the productivity and utilization of state-of-the-art DDC units used in plantation forestry. For this reason, the study was conducted over extended periods on multiple teams: that is the best way to secure reliable and generally representative benchmarks figures, which may integrate the inherent variability introduced by stand characteristics, team proficiency, seasonal fluctuations and many additional operational factors that may affect productivity and utilization. In particular, the study aimed at:

⇒ determining reference values for productivity and utilization

⇒ categorizing and analyzing downtime

⇒ gauging operator effect

⇒ determining the traits that characterize the most productive operators, for training purposes.

Such knowledge will allow accurate operation planning, which is crucial to modern precision management.

2. Materials and methods

The study covered three DDC units owned and managed by the Brazilian company Fibria Celulose. These machines were all the same model (Peterson

Pacific DDC 5000 H) and they all featured CAT 32 Acert engines with a maximum rated power of 839 kW. The machines were acquired in 2014 and have been operating since then on the large company estates in San Paolo State, Brazil. All machines were operated on a triple 8-hour shift schedule, all year long. The only significant interruptions in this work schedule were those required by periodic machine overhauls. Each machine was part of a different team or Unit, which included one or more clambunk skidders for supplying the DDC with a sufficient amount of whole tree feedstock. Chips were blown directly into road trains, with a capacity of 50 m^3 solid equivalent. While the skidders and the DDCs were owned and managed by the company, transportation was outsourced to private contractors.

All machines were constantly monitored for management purposes, using automatic data collection devices that transmitted position and activity data directly to the harvesting management central in real time. The proprietary data collection devices included a user interface, where the operator could enter specific notes. These included: operator ID (entered upon logging on the system); farm and compartment ID; the number on the bill of lading for each load being dispatched; an estimate of the volume of each load; the reason for any interruption in the work process – the latter described according to 39 predefined delay categories. All entries carried a time stamp, which allowed determining the exact duration of any work bouts and delay events. Periodically, this data base was updated by reconciling volume load estimates with the actual volumes measured at the mill, upon arrival. Plantation and tree size characteristics were obtained by integrating harvest plan data with the harvesting operation record, based on the farm and compartment ID included with each single record.

For the purpose of the study, the authors acquired the complete database for the three DDC units for three consecutive years, from 2015 to 2017. The database contained 194 253 unique records, representing a total of 77 045 hours of worksite time. During this time, the three machines produced ca. 60 000 loads, or 2.9 million m^3 of wood solid equivalent under bark (ub). The database represented 42 different operators and 598 compartments.

Before analysis, individual records were organized in different ways, depending on the objective of the analysis. In particular, results were summed as monthly totals when analyzing machine utilization, in order to reduce the typically erratic variability of delay events. The assumption was that utilization estimates would be more representative of long-term use if averaged over relatively long periods. In contrast, the analysis of net productivity was conducted at both the shift and the compartment level, to reflect the impacts of daily variation and stand characteristics. Results were split by unit, shift or operator, depending on the effect being explored from time to time. Delay records were grouped according to their general characteristics, in order to have fewer delay types than the original 39 categories, which would have been difficult to analyze and impossible to present in a reader-friendly format. Grouping was done based on the relevance of the specific delay cause and on the association of more delay types with one specific root cause and/or system component. The delay types that were especially frequent and represented a large proportion of total delay time were kept separate, while those that were sporadic and represented a relatively small proportion of total delay time were grouped with other delay types having similar characteristics.

The dataset was analyzed with SAS Statview 5.1 advanced statistics software, in order to check the statistical significance of any effects and trends. Before analysis, the data was tested for normality using Ryan-Noyer's test, and for homoscedasticity using Bartlett's test. If some of the data violated any of the parametric assumptions and the treatments on tests had few levels (as for Unit type or shift), then comparisons were conducted using non-parametric statistics and differences were pinned on specific treatments by repeating the same analyses for two treatments at a time, on all the treatment combinations. In this instance, the Kruskal-Wallis multiple comparison test and the Mann-Whitney unpaired comparison *U*-test were used, respectively. In contrast, if the treatments on test had more than few levels (as for operator effect), then an effort would be made to normalize data through transformation (LOG_{10}, square root, arcsine, etc.) and then use parametric techniques, such as the analysis of variance (ANOVA). Afterwards, differences were pinned on specific treatments using the Tukey-Kramer multiple comparison test.

Concerning operator effect, the analysis was restricted to 10 operators out of 42, because the 10 selected operators were the only ones who had worked for more than 18 months across the whole study period, while the others had either joined recently or had dropped out at a relatively early date. Focusing on the 10 »regulars« allowed the exploration of learning curves without incurring singularity errors (e.g. some operators being exclusively associated with some periods). Furthermore, operator work-months were considered valid and included in the analysis only if the operator had worked at least one week (or 40 scheduled hours) in that month.

The effect of shift work was explored for 2015 only, since all records for this year were clearly marked with the shift they belonged to. Given the large amount of data already available for 2015, it was assumed that any shift effects found over a whole year were likely to be generally representative of the three years, and therefore it was decided not to venture into the recalculation of shift factors for 2016 and 2017, which may have increased the risk of errors.

Regression analysis was used to test the significance of any relationships between productivity, utilization or delay incidence (dependent variables) and such influencing factors (independent variables) as time into the study, mean tree volume and tree characteristics (first rotation or resprout, introduced as indicator variables). Compliance with the statistical assumptions was checked through the analysis of residuals. In all analyses, the elected significance level was α<0.05.

Fig. 1 One of the study units at work. The picture shows the plantation as well as the whole operation, with a skidder moving whole trees to the DDC and a truck under the chipper spout for receiving its load of clean chips

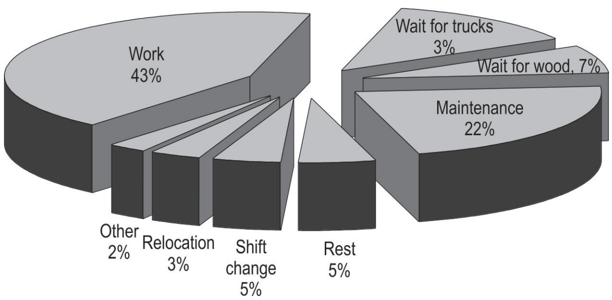


Fig. 2 Breakdown of total worksite time between productive work and delays

3. Results

The study covered 77 045 hours, equally spread over the three units. During this time, operators recorded 79 858 delay events, with an average duration of 0.55 hours per event. Delay time totaled 44 040 hours, and accounted for 57% of total worksite time. Mean utilization was therefore 43%.

Maintenance was the most important cause of delays, and accounted for 39% of total delay time, or 22% of total worksite time (Fig. 2). Waiting for trucks was the second most important cause of delays, representing 13% of total worksite time.

Mean productivity was 88 solid m^3_{ub} per productive machine hour (PMH) or 39 solid m^3_{ub} per scheduled machine hour (SMH), depending on whether delay time was excluded or included in the calculation.

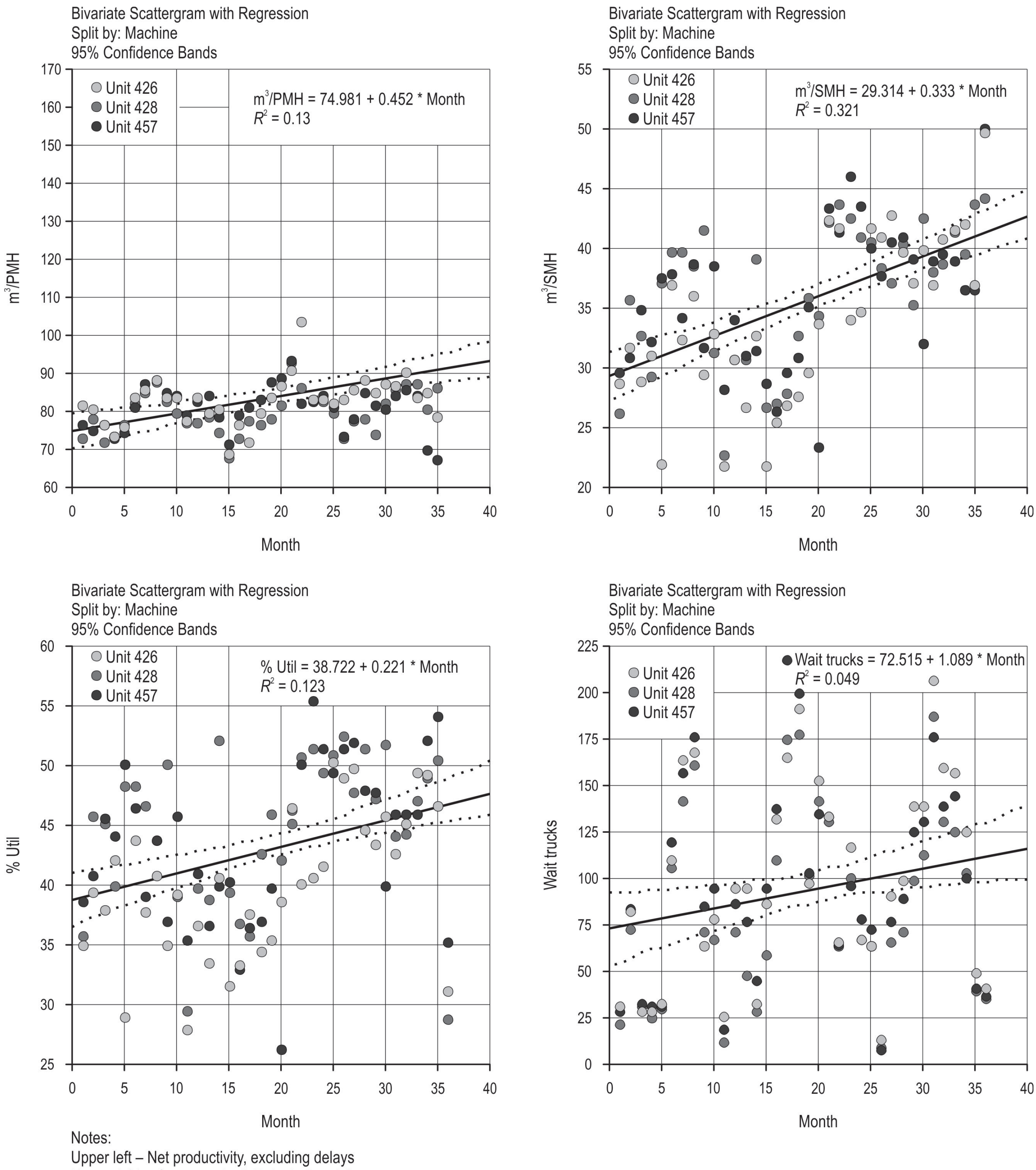
3.1 Time trends

The analysis of monthly totals per machine showed that neither worksite time nor productive time increased significantly over the study period (R^2=0.015 and –0.048, respectively). In contrast, productivity and utilization did show a steady increase over time (Fig. 3). The increase in utilization was due to a reduction in the mean duration of the single event (R^2=–0.105), rather than to a reduction in the frequency of events (R^2=–0.001). It is worth noting that such an important cause for delay as »waiting for truck« exhibited a fluctuating behavior that could best be described by a sinus curve and may underline a seasonal pattern. Interestingly enough, the time spent waiting for trucks did not change over the study period, and neither did the frequency of waiting events, their duration or the incidence of waiting for trucks over total work site time, as shown by the very low coefficient of determinations in Table 1.

Table 1 Coefficients of determination for the regressions associating delay (dependent variable) with total study duration (independent variable – from month 1 to month 36)

Delay	Incidence	Time	Events	Duration
	%	h month^{-1}	n°	h event^{-1}
Wait for trucks	0.071	0.049	0.071	0.008
Wait for wood	–0.460	–0.513	–0.314	–0.289
Maintenance	–0.033	–0.094	0.081	–0.230
Rest	–0.085	–0.143	–0.050	–0.044
Shift change	0.179	0.021	0.150	–0.092
Moving	0.036	–0.001	0.064	–0.059
Other	–0.013	–0.018	–0.001	–0.031

Note: »Other« includes: bogging down, assisting another machine, receiving instructions, checking, traffic, holiday, cleaning the road, planning meetings, etc.



Notes:
Upper left – Net productivity, excluding delays
Upper right – Gross productivity including delays
Lower left – Utilization (PMH/SMH)
Lower right – Waiting for trucks (h month^{-1})

Fig. 3 Time trends for productivity, utilization and waiting for trucks

In contrast, the time spent waiting for wood to be delivered to the DDC showed a steady decrease over the years, resulting from a marked reduction of both event frequency and single event duration. No main changes occurred for maintenance, although the coefficients of determination of the time-related regressions suggested an increase in the frequency of events accompanied by a reduction in the duration of the single events, as if interventions became lighter due to earlier interruptions of the work routine, before more serious maintenance interventions were required. In any case, the incidence of maintenance time over total worksite time remained unchanged.

Rest time showed a small but steady decrease, while shift change time increased for both incidence and event frequency, which seems difficult to explain. No main trends were recorded for moving time and other delay time.

3.2 Machine unit (team) effects

There were no significant differences between units for monthly production and total worksite time, although the analysis pointed at distinct work patterns. In particular, Unit 457 recorded a lower utilization than the other two units, but a higher net productivity – eventually leading to the same monthly production (Table 2). Repeated separately for each of the three years covered by the study, the analysis showed that Unit 457 had a significantly lower utilization than the others in 2015. In contrast, no significant utilization differences emerged for 2016 and 2017. Therefore, the grand mean representing Unit 457 over the whole study duration was heavily affected by an

Table 2 Median values of the main performance indicators for 3 Units (on a monthly basis)

Team		426	428	457	All
Volume	m^3_{ub}	27 361^a	25 625^a	24 221^a	25 387
Productive time	h	335^a	332^{ab}	297^b	321
Worksite time	h	731^a	740^a	734^a	735
Productivity	m^3_{ub} PMH^{-1}	80^a	82^{ab}	84^b	82
Productivity	m^3_{ub} SMH^{-1}	38^a	37^a	34^a	37
Utilization	%	46^a	45^a	40^b	44
Delay time	h	396^a	408^a	438^b	414
Delay events	n°	695^a	773^a	777^a	740
Delay events	h event^{-1}	0.60^a	0.52^a	0.56^a	0.55

Notes: m^3_{ub} – Cubic meters solid volume, under bark

PMH – Productive machine hours, excluding delays

SMH – Scheduled machine hours, including all delays

Data was analyzed with non-parametric techniques due to violation of the normality assumption

Different superscript letters on figures in the same line indicate statistically significant differences between medians for α<0.05

Table 3 Median values for delay incidence, time, frequency and duration by delay type and machine Unit

	Unit	Wait for trucks	Wait for wood	Maintenance	Rest	Shift change	Moving	Other
Incidence	426	9.9	5.3^a	20.3	5.4	4.6	3.2	2.0
% over total	428	12.5	5.0^a	20.8	5.1	4.3	2.9	1.5
Worksite time	457	12.7	7.9^b	20.3	4.8	4.5	3.4	1.4
	All	12.4	6.3	20.6	5.1	4.5	3.2	1.6
Time	426	71.3	35.5^a	146.8	38.6	33.3	22.2	13.9
h month^{-1}	428	91.3	35.8^a	148.7	35.4	30.9	20.8	10.6
	457	94.8	52.8^b	146.6	35.6	32.6	23.4	10.0
	All	89.8	42.9	147.3	36.4	32.2	22.5	10.7
Frequency	426	147	122^a	187	58	115	22	24
Events month^{-1}	428	172	149^{ab}	173	57	113	23	20
	457	196	194^b	168	54	101	26	23
	All	163	160	177	55	112	24	22
Duration	426	0.55	0.31	0.86	0.67	0.31	0.94^a	0.55
h event^{-1}	428	0.52	0.25	0.78	0.66	0.28	0.78^b	0.52
	457	0.50	0.28	0.97	0.65	0.31	0.87^{ab}	0.54
	All	0.52	0.28	0.86	0.66	0.30	0.90	0.54

Notes: Data was analyzed with non-parametric techniques due to violation of the normality assumption; different superscript letters on figures in the same column indicate statistically significant differences between the medians for different Units (α<0.05)

Superscript letters have been reported only for those groups where significant differences existed and not for the others, in order to minimize table clutter initial gap that was rapidly bridged through management interventions, but still left its mark on the final cumulated figures.

A deeper analysis of delay time suggested that the main differences were related to a different capacity to tackle such delay types as waiting for trucks and waiting for wood (Table 3). In particular, Unit 426 incurred a lower frequency of »wait for trucks« events, or 15% and 25% fewer events per month than recorded for units 428 and 457, respectively. That resulted in saving between 20 and 24 hours per month compared with the other two units, and translated into a lower incidence of »wait for trucks« delay time. Statistical analysis could not confirm the significance of this difference, and the results were considered suggestive, not conclusive.

Conversely, Unit 457 recorded between 20% and 60% more »wait for wood« delay events compared with the other two units, and spent an additional 17 hours per month waiting to be supplied by the skidders. This time, the difference was significant and the results could be taken as conclusive. Interestingly enough, the average duration of the single delay event did not change significantly with machine Unit for either »wait for trucks« or »wait for wood« delays. That was true for most delay types, except for moving, where significant differences existed between some machine Units.

Table 4 Mean values of the main performance indicators for 10 selected operators

	Productivity		Utilization
Operator	m^3_{ub} PMH^{-1}	m^3_{ub} SMH^{-1}	%
A	80.3^{ab}	34.7^{abc}	43.5^{abc}
B	85.6^{ab}	*39.1^{ac}*	46.3^{a}
C	81.6^{ab}	36.7^{abc}	45.6^{a}
D	83.8^{ab}	32.5^{abc}	38.7^{bc}
E	89.1^{a}	*39.5^{ac}*	44.7^{ac}
F	89.9^{a}	*37.3^{ac}*	41.8^{bc}
G	80.5^{ab}	35.3^{abc}	44.5^{ac}
H	77.9^{b}	*37.8^{ac}*	*48.6^{abc}*
I	88.1^{ab}	34.8^{bc}	39.7^{bc}
L	81.2^{ab}	34.3^{b}	42.3^{bc}
Mean	83.9	36.2	43.5

Notes: m^3_{ub} – Cubic meters solid volume, under bark

PMH – Productive machine hours, excluding delays

SMH – Scheduled machine hours including all delays

Different superscript letters on figures in the same line indicate statistically significant differences between medians for α<0.05

The general homogeneity of mean event duration for each delay type was taken as an indicator of consistent understanding of delay cause classification among the operators who were responsible for data recording, which represented an indirect assurance of good quality data.

3.3 Operator effect

The ten operators matching the study requirements represented a relatively homogenous group, and yet the analysis of data showed significant differences for productivity and utilization. Operators E and F achieved the highest net productivity, while operator H achieved the lowest (Table 4). However, operator H also achieved a significantly higher utilization than most other operators, and placed among the four most productive operators in terms of actual gross productivity, together with operators B, E and F. This result clearly showed that there are different ways to obtain high productivity: fast working pace is one, but consistent high utilization is equally good.

In relative terms, the most productive operator exceeded mean net productivity, gross (scheduled) productivity and utilization figures by 7%, 9% and 11%, respectively. The gap between the highest and the lowest performers was 15%, 22% and 26% for the above-mentioned indicators, in the same order. This difference was calculated taking the figures for the lowest performer as a basis.

However, the analysis of variance (ANOVA) showed that differences between operators accounted for only 5% of the total variability in the data and that the effect of time into the study (monthly sequence)

Table 5 ANOVA for the effect of operator and time (independent variables) of productivity and utilization (dependent variables)

	Effect	*DF*	*SS*	η^2	*F*-Value	*P*-Value
Productivity	Operator	9	3683	0.05	2.239	0.0194
m^3_{ub} PMH^{-1}	Year	1	5739	0.08	31.4	<0.0001
	Interaction	9	3132	0.04	1.904	0.0506
	Residual	326	59 582	0.83	–	–
Productivity	Operator	9	915	0.05	2.865	0.0029
m^3_{ub} SMH^{-1}	Year	1	3963	0.23	111.73	<0.0001
	Interaction	9	470	0.03	1.473	0.1567
	Residual	326	11 562	0.68	–	–
Utilization	Operator	9	1092	0.05	2.405	0.0119
%	Year	1	2089	0.10	41.405	<0.0001
	Interaction	9	329	0.02	0.725	0.6862
	Residual	326	16 445	0.82	–	–

was twice as strong as that caused by operator selection (Table 5). That supported the notion of a steady improvement over time, which may also have reduced initial differences. Furthermore, the interaction factor »operator x time« was never significant, indicating that all operators improved their performance over time, and at similar rates.

Again, detailed analysis of delay time was used for identifying the strategies implemented by top operators for achieving superior results. The incidence of different delay types over total worksite time was significantly different among operators, while lower variation was found concerning the duration of delay events, except for shift change (Table 6). Some operators emerged for the especially high (or low) representation of specific delay types. This was the case of operator B, who recorded a much lower incidence of truck waiting compared with the others, or of operator D, who suffered from a particularly high incidence of »wait for wood« delays. It is worth mentioning that operator D was the lowest performer in the group for both scheduled productivity and utilization (Table 6). Detailed analysis of delays showed that this operator was with the group characterized by a relatively high incidence of »maintenance«, »rest« and »other« delays – besides the already mentioned issue with the »wait for wood« downtime. Conversely, the operator who recorded a significantly higher utilization level than all the others and who positioned among the four most productive operators (i.e. operator H), was also the operator who recorded a lower than average incidence for »maintenance«, »rest« and »other« delay types, besides achieving the lowest figure for »wait for wood« downtime. Differences between the two operators were statistically significant for »wait for wood« and »rest«, but not for »maintenance« and »other« delay time, possibly due to the large variability in the monthly distribution of planned and unplanned maintenance interventions, and in the erratic occurrence of typically undefined »other« time. In any case, there was an exact match in the delay types that characterized both the best and the poorest performer, the main difference being that one managed to contain their effect, while the other did not.

Regression analysis showed that there was a general agreement among operators in some trends, but not in others (Table 7). For all operators, the relationship between time in service and incidence of »wait for wood« delays was characterized by relatively high coefficient of determination and a minus sign, indicating a general and marked improvement in system balance. The same was true for »rest« delays, which showed a generalized decreasing trend. Conversely, the incidence of »wait for truck« delays followed variably growing trends: for some operators the variation over time was minimal, for others it was somewhat more significant, but in no case the trend was a decreasing one, which should flag this delay type as an

Table 6 Mean values for delay incidence and duration by delay type and operator

	Wait for trucks		Wait for wood		Maintenance		Rest		Shift change		Moving		Other	
Operator	%	h event^{-1}	%	h event^{-1}	%	h event^{-1}	%	h event^{-1}	%	h event^{-1}	%	h event^{-1}	%	h event^{-1}
A	11.9^{a}	0.47^{a}	6.9^{a}	0.26	21.1^{ab}	0.84^{a}	6.8^{a}	0.70	4.6	0.27^{a}	3.0^{ab}	0.91	2.1^{ab}	1.03^{a}
B	6.7^{b}	0.63^{b}	7.0^{ab}	0.35	22.8^{ab}	0.85^{a}	6.2^{a}	0.67	4.4	0.30^{ab}	4.2^{a}	1.02	2.3^{ab}	0.86^{ab}
C	12.9^{a}	0.55^{ab}	6.1^{a}	0.31	21.4^{ab}	0.88^{a}	4.3^{b}	0.63	4.2	0.26^{a}	3.4^{ab}	0.83	2.0^{ab}	0.91^{ab}
D	12.7^{a}	0.46^{a}	**10.7^{b}**	0.38	22.2^{ab}	0.98^{ab}	**6.0^{a}**	0.71	4.7	0.34^{b}	2.6^{b}	0.84	2.4^{ab}	0.58^{ab}
E	17.1^{a}	0.52^{ab}	5.7^{a}	0.25	17.7^{a}	0.94^{ab}	4.7^{b}	0.70	4.7	0.34^{b}	2.7^{ab}	0.79	2.6^{ab}	0.82^{ab}
F	14.6^{a}	0.53^{ab}	8.5^{ab}	0.36	20.9^{ab}	1.20^{b}	4.2^{b}	0.64	4.6	0.33^{ab}	3.1^{ab}	0.83	2.4^{ab}	0.82^{ab}
G	12.6^{a}	0.57^{ab}	5.1^{a}	0.27	21.7^{ab}	0.87^{a}	6.0^{a}	0.70	4.1	0.32^{ab}	3.4^{ab}	1.12	2.6^{ab}	0.70^{ab}
H	16.3^{a}	0.53^{ab}	**3.8^{a}**	0.32	17.6^{a}	0.85^{a}	**4.3^{b}**	0.66	5.2	0.29^{ab}	3.2^{ab}	0.98	1.0^{a}	0.65^{ab}
I	14.1^{a}	0.56^{ab}	6.5^{ab}	0.34	24.0^{b}	1.06^{ab}	5.1^{b}	0.68	4.8	0.36^{b}	3.0^{ab}	0.99	2.8^{b}	0.84^{ab}
L	11.7^{a}	0.47^{a}	8.9^{ab}	0.29	21.2^{ab}	0.76^{a}	5.7^{a}	0.66	4.3	0.27^{a}	3.1^{ab}	0.90	2.7^{ab}	0.50^{b}
All	13.0	0.53	7.0	0.31	21.1	0.92	5.3	0.67	4.6	0.31	3.2	0.92	2.3	0.77

Notes: Different superscript letters on figures in the same column indicate statistically significant differences between the means for the different operators (α<0.05).
Superscript letters have been reported only for those groups where significant differences existed and not for the others, in order to minimize table clutter. In bold are the references for the operators who recorded the highest (operator H) and lowest (operator D) utilization figures, and those figures for which the differences are statistically significant

Table 7 Coefficients of determination for regressions associating delay time types (dependent variable) with total study duration (independent variable – from month 1 to month 36) for each individual operator

Operator	Wait for Trucks	Wait for wood	Maintenance	Rest	Shift change	Moving	Other
A	0.060	–0.450	0.090	–0.098	–0.129	0.021	0.001
B	0.141	–0.115	–0.071	–0.033	0.342	–0.001	–0.028
C	0.001	–0.294	0.022	0.051	0.364	0.011	–0.005
D	0.106	–0.112	–0.103	–0.114	0.102	0.003	–0.119
E	0.009	–0.403	0.009	–0.187	0.001	0.116	–0.005
F	0.064	–0.451	–0.001	–0.038	–0.005	0.012	–0.049
G	0.001	–0.308	–0.021	0.001	0.356	–0.001	–0.021
H	0.045	–0.316	–0.036	–0.254	–0.149	–0.088	0.002
I	0.001	–0.487	0.001	–0.006	0.001	0.044	0.007
L	0.166	–0.369	–0.001	–0.146	0.002	–0.001	–0.005

important and yet unsolved issue. Finally, the trends for »shift change«, »moving« and »others« were extremely variable. They seemed to be significant for some operators, not significant for most, and they could be either increasing or decreasing, with no discernible patterns. The trend for »maintenance« time was likely the most undefined, and was characterized by very weak coefficients of determination: the only exception here was operator D, for whom maintenance time seemed to decrease more significantly than for the rest. This may suggest a strong resolution to increase utilization, since this operator achieved the lowest overall utilization figures among the ten operators in the study. The hypothesis of a deliberate effort to improve one's own performance could be confirmed by the fact that this operator also showed meaningful decreasing trends for the incidence of other delay types, such as »rest« and »other«.

3.4 Effect of shift work

Data recorded in 2015 were separated by work shift, which allowed testing the effect of shift work on productivity and utilization. Obviously total worksite time did not change with shift type, since all shifts were scheduled for an overall duration of 8 hours. However, utilization was significantly lower for the day shift (i.e. shift 2, beginning at 8 am and ending at 4 pm), compared with the others. Productive time was ca. 10% shorter for the day shift, as delay time expanded (Table 8). In fact, significantly fewer delay events were recorded during the day shift compared with the other two shifts, but these events also had a significantly longer duration. While net work productivity was the same regardless of shift type, gross scheduled productivity was lower for the day shift as a result of lower utilization.

Table 8 Median values of the main performance indicators for 3 shifts (on a monthly basis)

Shift	n°	1	2	3
Shift	Type	Night	Day	Evening
Volume	m^3_{ub}	8056[ab]	7022[a]	8347[b]
Productive time	h	102[a]	91[b]	103[a]
Worksite time	h	246[a]	247[a]	248[a]
Productivity	m^3_{ub} PMH^{-1}	80[a]	81[a]	82[a]
Productivity	m^3_{ub} SMH^{-1}	33[a]	29[b]	35[a]
Utilization	%	42[a]	38[b]	43[a]
Delay time	h	144[a]	156[b]	145[a]
Delay events	n°	271[a]	218[b]	252[a]
Delay events	h event^{-1}	0.53[a]	0.72[b]	0.58[a]

Notes: Data were only available for 2015, and they may not represent the other two years of the study; data was analyzed with non-parametric techniques due to violation of the normality assumption; different superscript letters on figures in the same line indicate statistically significant differences between medians for α<0.05

A detailed analysis of delay time helped understanding the reason of such an unexpected finding. The main cause for the lower utilization recorded for the day shift was a much larger incidence of maintenance delays (Table 9). The day shift contained over twice as many maintenance hours than any of the other shifts: maintenance stops were 20 to 33% more frequent and lasted 60% longer during the time between 8 am and 4 pm, compared with the rest of the day. Apparently, major maintenance work occurred most often during the day shift. That caused a dramatic drop in machine utilization, which could not be fully offset by the significant reduction of truck waiting and shift change

Table 9 Median values for delay incidence, time, frequency and duration by delay type and shift

	Shift	Wait for trucks	Wait for wood	Maintenance	Rest	Shift change	Moving	Other
Incidence	1	16.4[a]	10.1	14.8[a]	2.4[a]	7.3[a]	2.1[a]	1.2
% over total	2	4.9[b]	9.2	32.7[b]	6.5[b]	0.9[b]	3.0[b]	2.3
Worksite time	3	7.7[c]	11.4	17.2[a]	7.2[b]	3.9[c]	3.2[b]	1.1
	All	6.4	7.7	20.8	6.2	4.0	2.8	1.8
Time	1	38.3[a]	24.8	35.8[a]	6.0[a]	17.7[a]	5.1[a]	2.9
h month^{-1}	2	11.5[b]	22.4	80.3[b]	16.1[b]	2.2[b]	7.4[b]	5.4
	3	18.7[c]	28.3	39.8[a]	17.2[b]	9.6[c]	7.6[b]	2.6
	All	15.3	25.3	50.7	14.9	9.6	6.6	4.3
Frequency	1	56[a]	74	45[a]	10[a]	54[a]	6.0[a]	6[a]
Events month^{-1}	2	22[b]	70	60[b]	23[b]	9[b]	8.0[b]	11[b]
	3	41[a]	79	49[a]	26[b]	31[c]	8.0[b]	4[a]
	All	39	74	53	21	31	7.0	7
Duration	1	0.58[a]	0.32	0.83[a]	0.64	0.33[a]	0.95	0.50
h event^{-1}	2	0.36[b]	0.33	1.35[b]	0.71	0.23[b]	1.04	0.57
	3	0.47[c]	0.35	0.83[a]	0.65	0.29[c]	0.96	0.57
	All	0.47	0.33	1.03	0.68	0.30	0.98	0.55

Notes: Data was analyzed with non-parametric techniques due to violation of the normality assumption; different superscript letters on figures in the same column indicate statistically significant differences between the medians for different Units (α<0.05).
Superscript letters have been reported only for those groups where significant differences existed and not for the others, in order to minimize table clutter

delays, both of which were shortest and least frequent for the day shift. Truck waiting and shift change delays were longest and most frequent during the night shift, between 0 am and 8 am. During this shift, rest and moving stops were least frequent, causing a significant reduction of the respective delay time.

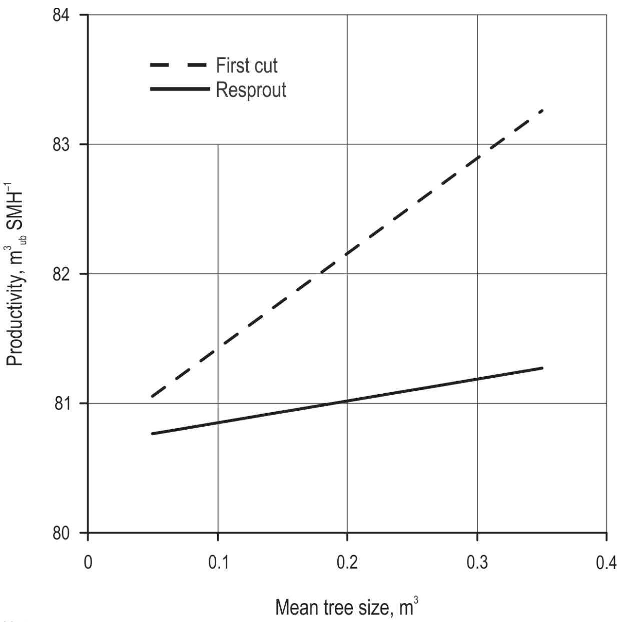
The analysis of variance (ANOVA) showed that unit (machine ID) had a stronger impact on machine utilization than work shift (15% vs. 10% of total variability), while both effects were equally strong when it came to scheduled productivity (10% each).

3.5 Net productivity

Several attempts were made at modeling net productivity as a function of significant independent variables. The analyses were repeated on a single shift basis, on a compartment basis and separately for different years. The idea was that net productivity could be better analyzed on shorter periods than on a whole month, and that such a more detailed investigation would yield additional details that could not be gleaned from the analysis of monthly averages.

The analyses did confirm the presence of small but significant differences between different units and operators, but that added nothing new to what had already been obtained from the analysis of monthly averages. The only new information was about the effect of management regime: the analyses indicated that net productivity incurred a 2% drop (from 82.1 to 80.7 $m^3{}_{ub}$ PMH^{-1}) when the machines negotiated resprouts rather than trees coming from a first cut, which corresponded to anecdotal evidence about feeding difficulties caused by the typical pistol-butts that characterize resprouts.

Detailed analysis at the shift or the block level was expected to materialize the effect of stem size on net productivity, but results were inconclusive. Most attempts could not confirm the significance of this effect, and those that managed to do so indicated that the effect was very weak, anyway. Regression analysis produced several models, none of which was particularly strong or significant. The model presented in Fig. 4 was the most viable, but it had a very weak explanatory power (R^2=0.01) and was reported just as



Note:
The relationship is described by the following equation, with an R^2 of only 0.01 : m^3u_b PMH^{-1} = 80.676 + 7.374 Mean tree size (m^3_{ub}) – 5.670 Mean tree size (m^3_{ub})
* Dummy resprout (= 1 if resprout, = 0 is first cut)
m^3_{ub} – cubic meters under bark, solid volume
PMH – productive machine hours, excluding all delays

Fig. 4 Tentative equation for predicting net productivity per hour (m^3_{ub} PMH^{-1})

a general suggestion of what the relationship between productivity, tree size and management type could look like.

4. Discussion

4.1 Reliability, accuracy and generalization

The sheer amount of data makes the results of this study exceptionally robust, but some questions remain about their accuracy and their potential use as a general reference.

Operator input does raise the question of accuracy, as different operators may have categorized the same time element in different ways. Similarly, reconciling different data streams (such as time stamps from the machines and load volumes from the mill) may have resulted in the occasional matching error, which must have reduced the accuracy of study results. This seems confirmed by the presence of outliers, possibly resulting from attribution and/or data matching errors. Yet, despite the many outliers, results are consistent and trends seem quite clear. Furthermore, the fact that similar delay events have similar mean duration regardless of operator or year, points at a good general understanding, where attribution error may have been rare and randomly distributed, rather than frequent and systematic.

On the other hand, one may reasonably doubt about the capacity of this study to provide a general representation of DDC operations in fast-growing eucalypt plantations. The model represented in this study is that of fine-tuned, closely-supervised operations in rationally-managed, high-productive tree farms. Therefore, these results are likely to represent a best case scenario, rather than the norm: they can be extended to any plantations offering similarly favorable condition, but they may be too optimistic for medium-quality plantations harvested by small-scale contractors, without the same high levels of support and supervision encountered in this study.

4.2 Comparison with previous studies

The authors found three other studies dealing specifically with the use of DDCs in eucalypt plantations, and namely: Ghaffaryian et al. 2013, McEwan et al. 2018, Spinelli et al. 2002.

These studies indicated a net productivity between 35 and 55 m^3_{ub} PMH^{-1}, which is much lower than reported here. The reference that approaches the high net productivity levels recorded in this study is a recent paper that reports 75 m^3_{ub} PMH^{-1} as the mean net productivity of a stand-alone chain-flail delimber, without integral chipper but much similar to a DDC 5000 H in all other characteristics (McEwan et al. 2017).

These comparisons prove the points made before in chapter 4.1: the high productivity levels reported in this study are only valid for fine-tuned, closely-supervised operations in high-productive plantations, and they maybe too optimistic for the cases presented by Ghaffaryian et al. (2013) or Spinelli et al. (2002). Those were conducted in lower-quality stands established in Australia and North America with *E. globulus*, not improved hybrids, and they described contracted operations, not centrally-managed ones. The very fact that only another South American study (McEwan et al. 2017) gets much closer to the figures in this paper may confirm the effect of superior tree quality on machine productivity. The genetically improved eucalypts used in South America are taller, straighter and carry many fewer branches than *Eucalyptus globulus*, and these characteristics are quite likely to favor machine productivity, especially when it comes to debranching (Campinhos et al. 1998).

Another main difference between the figures in this paper and those reported in recent literature concerns utilization, which is much lower in this study than in the previously-quoted ones. Literature figures range from 55% to over 90%, and are twice as high as recorded in this study. Such difference can be explained by at least two main causes, not exclusive of each other. First, one may surmise that the operations in this study were less efficient than ordinary. Second, it is possible that the previous studies missed a significant share of the actual delays, thus overestimating utilization.

Certainly, all previous studies represented short-term experiments, lasting between 4 and 45 hours at most, and it is very likely that they missed at least some of the main delay events. Furthermore, these studies excluded preparation (shift change) and major maintenance interventions from the time record, which must have inflated utilization. In contrast, the present study covered all time, 24 hours per day, during which all interruptions of the work routine had to be motivated. Therefore, this study is fully inclusive, and in that regard has similarities with classical time-use studies – which is not the case for the quoted references (Stinson 1999).

Low efficiency is also a possibility, but that sounds unlikely for the closely-supervised operations covered in this study. Of course there must be margins for improvement, or the study would not show a steady increase of utilization over time. Yet, continuous improvement is the witness to a constant attention for operational efficiency, which brings us back to the effects of close supervision (Bunker and Wijnberg 1988).

In essence, there is every reason to believe that the utilization figures presented in this study represent real operations better than the more optimistic estimates reported in the literature, which stem from short-term studies and do not include all delays incurred in the long run.

4.3 Managing delays

The study clearly shows that utilization is especially impacted by machine maintenance and system balance: both are especially relevant to complex machines and »hot« harvesting systems, with close interaction between different elements along the supply chain. Machine maintenance and interaction delays (i.e. waiting for wood and waiting for trucks) account for over 40% of total worksite time, or for 75% of total delay time. Therefore, it just makes sense to target improvement efforts to these two main groups of delays, and certainly that is what company managers must have done. Management attempts have been particularly successful with restoring balance upstream, as shown by a steady and significant reduction of the time waiting for wood. So far, less success has been obtained with improving machine balance downstream, or with reducing the time spent on maintenance.

Improving balance with the truck fleet is complicated by the fact that transportation is the only element in the supply chain that is outsourced, and cannot be managed directly. Therefore, any adjustments must be negotiated with the contractors and require time, which may extend the delay before one may see any tangible results. This study has the double merit of highlighting the absence of any progress with truck fleet issues, and of revealing the oscillating pattern of truck waiting delays. A deeper study of this pattern may help understanding the issue, and point at the measures for addressing it. Obviously, if truck waiting time is a minor problem at some moments, it becomes a major one during other moments: therefore observing the differences between the two cases may offer precious insights on what makes the system work, and what does not. Furthermore, the lower incidence of truck delay time during the day shift compared with the other shifts may offer additional clues for developing improvement measures.

Similarly, a deeper analysis of maintenance activities may help identifying specific opportunities for improvement. All machines require some maintenance, but service time can be decreased in various ways, which go from a reorganization of the maintenance routines to a different sourcing of the needed spares. At this stage it is impossible to know what could be improved, but a harder look into the maintenance records may provide some useful clues. A deeper analysis of maintenance delays may also shed light on the effect of shift work on operation efficiency, since most of this effect seems to originate from a larger proportion of maintenance being included with the day shift, compared with the other shifts.

In that regard, the study seems to negate any of the productivity losses generally attributed to shift work, which experts estimate at over 10% (Folkard and Tucker 2003, Nicholls et al. 2004). This may indicate a proper management of shift work, capable of addressing such important issues as supervision, lighting, congestion and material requirements (Hanna et al. 2008).

4.4 Operator effect

The study clearly shows that operator proficiency has a significant effect on overall productivity, which was expected and is generally supported by the existing literature on the subject. In particular, the between-operators variation shown here is similar to that reported by Mola et al. (2010) for chippers, but much smaller than the figures published by Ovaskainen et al. (2004) and Kärhä et al. (2004) for harvesters. A case could be made about the direct relationship between task complexity and the impact of operator effect, which may be supported by the intermediate operator variability figures recently published by Engelbrecht et al. (2017) for excavator-based grapple yarders – assuming the latter are simpler to operate than a harvester, but more complex than a chipper. This is a plausible theory, but it may put too much emphasis on operator dexterity, while both the present study and the study by Engelbrecht et al. (2017) indicate that the best performers are often those with superior time management skills rather than exceptional dexterity. Best operators excel for good organization, rather than fast work pace: this is one of the key finding of this study, which also offers tantalizing glimpses into the possible association between work pace and maintenance needs, when it points at operator H as the one characterized by the lowest net productivity, the highest utilization levels and the lowest incidence of maintenance time and stops. The alignment of these three factors may support the notion that a lighter use of the machine eventually results in lower maintenance needs, thus offsetting a slower work pace. Of course, further evidence may be necessary before this finding can be taken as generally representative, but the fact itself represents a powerful argument for targeting time management and utilization rather than net productivity in any future operator training programs.

Furthermore, the study indicates that the most and least efficient operators are respectively best or worst at managing the same delay types, which points at the specific subjects to be included in the eventual training efforts. Of course, one has to be careful about interpreting the meaning (and mechanisms) of operator effect. Taken at face value, the term may imply exclusive operator responsibility, which assumes the DDC operator has control over all causes of delay. Even a very limited experience of field operations is enough to see how wrong such assumption must be: the operator on the machine seat is only one element of a complex system and he can only manage the frequency and duration of some delay events. More is outside of his control. Therefore, the poor rating of one operator may actually denounce the association of this operator with other operators (upstream or downstream) or with specific work conditions that limit his productivity, despite all good intentions and efforts. High operator efficiency is the result of good management as much as of personal capacity and motivation (Deming 1981). The fact that all operators in this study showed constant productivity increases is the witness to deliberate efforts made by management to advance overall operational efficiency.

4.5 Modeling

A major disappointment came from the inability of this study to determine a significant relationship between net productivity and tree size, despite all efforts. There are several reasons for such disappointing result, and namely:

- ⇒ the effect of errors and/or approximations in reconciling delivered volumes with shifts, as loads reaching the mill the next day could be erroneously associated to that day, while they were produced the day before
- ⇒ the differences between the actual tree size processed by the machines and the inventory figures used in the records
- ⇒ the limited variation in tree size inherent to uniform, even-age, pure clonal plantations, designed for harvesting as soon as the pre-determined tree size target has been reached
- ⇒ the dampening effect of mass handling, which is deployed for the specific purpose of evening out tree size differences in small tree harvesting.

Comfort can be obtained from noting that none of the previous DDC studies was able to produce a strong productivity model (McEwan et al. 2018), and that some authors even renounced estimating one, stating that mass handling made it impossible to discern any tree size effects (Mooney et al. 2000). While all these causes may have contributed in some degree to obscuring the relationship between productivity and stem size, they were unable to conceal the effect of stand management, which emerged quite clearly from the analysis and confirmed the anecdotal evidence already reported in Spinelli et al. (2002) about the handling difficulties incurred with resprouts and due to their marked pistol butts.

When read against the background of the many significant findings obtained from the study, failure to produce any meaningful relationship between productivity and tree size may be taken as an indication that tree size is not among the key elements affecting operational efficiency, at least within the range of tree sizes normally recovered from fast-growing pulpwood plantations. Therefore, improvement efforts should prioritize other strategies than tree size manipulation.

These results may contribute to the current debate about the future of automated and manual time study techniques, as automatically-captured data become increasingly available (Olivera et al. 2016). Once more, automatic data collection has showed its remarkable potential for capturing large amounts of data, and its limitations when it comes to accuracy and detail (Strangard et al. 2013). That highights the benefits of a mixed approach, where automatically-captured data are supplemented with manual samples (Košir et al. 2015).

5. Conclusions

Through the analysis of an exceptionally large database, this study offers robust benchmark figures for the performance of DDC units used in fast-growing eucalypt plantations. Results point at high productivity, relatively low utilization and steady improvement over time. The study also quantifies how productivity and utilization vary between different shifts, units and operators. The quality of automatically-captured data is good enough for detecting significant trends and differences, despite the errors possibly incurred when categorizing specific events or reconciling separate data streams. The exceptionally favorable work conditions offered by South American eucalypt plantations raise a critical question about the possibility of extending these results to other conditions, at least to some extent. While the exact productivity figures may reflect specific conditions only, the dynamics revealed in this study may have general validity and could offer precious insights for rationalizing a whole range of similar operations.

Acknowledgments

This project has been partly supported by the Bio Based Industries Joint Undertaking under the European Union's Horizon 2020 research and innovation program under grant agreement No 745874 »Dendromass for Europe« (D4EU). The authors also thank Dr. Giovanni Aminti for his assistance with data organization and pre-processing.

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Received: April 30, 2018
Accepted: June 17, 2018